a scan for the given clinical problem, such as a lung scan. The scan results in scan or image data that may be processed to generate an image of the interior of the patient on the display **500**. The scan or image data may represent a three-dimensional distribution of locations (e.g., voxels) in a volume of the patient. In another embodiment, the image data may represent a two-dimensional distribution of locations (e.g., pixels) in a volume of the patient.

[0087] The image processor **502** is a control processor, a general processor, a digital signal processor, a three-dimensional data processor, a graphics processing unit, an application specific integrated circuit, a field programmable gate array, an artificial intelligence processor or accelerator, a digital circuit, an analog circuit, combinations thereof, or other now known or later developed device for processing medical image data. The image processor **502** is a single device, a plurality of devices, or a network. For more than one device, parallel or sequential division of processing may be used. Different devices making up the image processor **502** may perform different functions. In one embodiment, the image processor **502** is a control processor or another processor of a medical diagnostic imaging system, such as one of the medical imagers **506**. The image processor **502** operates pursuant to stored instructions, hardware, and/or firmware to perform various acts described herein.

[0088] In one embodiment, the image processor **502** is configured to train one or more machine learning networks. Based on a network architecture and training data, the image processor **502** learns features for encoders, decoders, discriminators, generators, or other network parts to train the network. A multi-task generator is trained using nonaligned pairs of images (e.g., decomposed pairs of images) and corresponding losses for two or more tasks. One task is deformation field prediction. The other task uses data unlabeled for outcome, such as radiomic features, segmentation, non-image data, and/or other information that may be more commonly available than deformation field and/or may be derived from the available images.

[0089] Alternatively or additionally, the image processor **502** is configured to apply one or more machine-learned generative networks or generators. For example, the image processor **502** applies scan data from the first imager **506***a* and the second imager **506***b* (e.g., corresponding to a same patient and a same region of interest) to a machine-learned multi-task network. The network predicts a dense deformation field for registration between a moving image and a fixed image in response to the input of the moving image and the fixed image. The network may include an encoder of an autoencoder trained in an unsupervised manner and a fully-connected network configured to receive an output of the encoder to predict the dense deformation field. The encoder was trained with a decoder of the autoencoder to estimate an input from the output of the encoder in training in the unsupervised manner.

[0090] The image processor **502** is configured to register and display the moving image and the fixed image. The registered moving image and fixed image are displayed for, for example, decision support.

[0091] The display **500** is a CRT, LCD, projector, plasma, printer, tablet, smart phone or other now known or later developed display device for displaying the output, such as an image with an outcome prediction.

[0092] The scan data, training data, network definition, features, machine-learned network, deformation field, warped image, and/or other information are stored in a non-transitory computer readable memory, such as the memory **504**. The memory **504** is an external storage device, RAM, ROM, database, and/or a local memory (e.g., solid state drive or hard drive). The same or different non-transitory computer readable media may be used for the instructions and other data. The memory **504** may be implemented using a database management system (DBMS) and residing on a memory, such as a hard disk, RAM, or removable media. Alternatively, the memory **504** is internal to the processor **502** (e.g. cache).

[0093] The instructions for implementing the training or application processes, the methods, and/or the techniques discussed herein are provided on non-transitory computer-readable storage media or memories, such as a cache, buffer, RAM, removable media, hard drive or other computer readable storage media (e.g., the memory **504**). Computer readable storage media include various types of volatile and nonvolatile storage media. The functions, acts, or tasks illustrated in the figures or described herein are executed in response to one or more sets of instructions stored in or on computer readable storage media. The functions, acts or tasks are independent of the particular type of instructions set, storage media, processor or processing strategy and may be performed by software, hardware, integrated circuits, firmware, micro code and the like, operating alone or in combination.

[0094] In one embodiment, the instructions are stored on a removable media device for reading by local or remote systems. In other embodiments, the instructions are stored in a remote location for transfer through a computer network. In yet other embodiments, the instructions are stored within a given computer, CPU, GPU or system. Because some of the constituent system components and method steps depicted in the accompanying figures may be implemented in software, the actual connections between the system components (or the process steps) may differ depending upon the manner in which the present embodiments are programmed.

[0095] While the present invention has been described above by reference to various embodiments, it should be understood that many changes and modifications can be made to the described embodiments. It is therefore intended that the foregoing description be regarded as illustrative rather than limiting, and that it be understood that all equivalents and/or combinations of embodiments are intended to be included in this description.

1. A method for unsupervised multi-modal image registration, the method comprising:

acquiring a first image generated by a first medical imaging modality;

acquiring a second image generated by a second medical imaging modality, the second medical imaging modality being different than the first medical imaging modality;

generating a prediction of deformation fields between the first image and the second image, the deformation fields generated by a machine-learned generator having been trained in domain-invariant space with machine-learned discriminators having been trained in image space; and

registering the first image and the second image using one of the predicted deformation fields.